Journal of Arid Environments 152 (2018) 83–86

Contents lists available at ScienceDirect

Journal of Arid Environments

journal homepage: www.elsevier.com/locate/jaridenv

Vegetation's role in controlling long-term response of near ground air temperature to precipitation change in a semi-arid region

Yu Hui[a], Quan Zhang[a,*], Chong-Yu Xu[a,b], Lihua Xiong[a], Jie Chen[a], Ping Xie[a]

[a] State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan, China
[b] Department of Geosciences, University of Oslo, Oslo, Norway

ARTICLE INFO

Keywords:
Climate change
Land-atmosphere interaction
Precipitation
Temperature
Vegetation

ABSTRACT

The response of near ground air temperature to changing precipitation regimes has received extensive attentions in climate change studies. In semi-arid and arid regions, the mean annual temperature correlates negatively with precipitation. However, it remains unclear to what extent one unit change of precipitation can trigger temperature change (i.e., the temperature sensitivity to precipitation). Taking a semi-arid region in Northwest China as a study area, we quantitatively investigated the temperature sensitivity to precipitation change. Further analysis shows that the temperature sensitivity correlates well with the Normalized Difference Vegetation Index (NDVI), indicating that vegetation plays an important role in controlling the long-term temperature sensitivity to precipitation change. Specifically, different land covers show significant differences in temperature sensitivity, with bare soil generally having a higher sensitivity while more densely vegetated areas such as forest and grassland having lower sensitivity values. This implies that vegetation contributes to reducing the temperature sensitivity to precipitation change through the land surface-atmosphere interaction in semi-arid and arid regions.

1. Introduction

Near ground air temperature (T) is a variable of the land surface energy transfer process controlled by various local properties including solar radiation, water availability, and land cover types. In semi-arid and arid regions where temperature is largely regulated by precipitation, special attentions have been paid to the high temperature associated with drought events (Yin et al., 2014). The response of temperature to precipitation change results from land surface-atmosphere interaction, in which vegetation plays an important role (Pielke et al., 1998); naturally, vegetation has been widely recognized as a key factor in regulating the near ground air temperature magnitude (Bonan, 1997; Peng et al., 2014). However, it remains unclear whether or not vegetation regulates the long-term temperature sensitivity to precipitation change. Moreover, we know little about the extent to which air temperature will increase/decrease in accordance with a given decrease/increase in precipitation in semi-arid and arid regions. Lacking such knowledge limits our ability to predict extreme temperature events in these regions, particularly at a time when global precipitation is projected to change in most parts of the world (Stott, 2016).

In semi-arid and arid regions, mean annual temperature correlates negatively with precipitation (Yin et al., 2014), with reduced evaporative cooling effect well explaining the relatively higher temperature during drought. Meanwhile, vegetation greening has been suggested to cool down local environment (Peng et al., 2014; Shen et al., 2015) through enhanced evaporative cooling, justifying the role of vegetation in regulating local energy balance (Findell et al., 2009; Wang and Dickinson, 2012). With land cover dynamic being widely recognized to regulate temperature, whether it controls the temperature sensitivity to precipitation change has rarely been explored, framing the purpose of this study. Considering the important role of vegetation plays in controlling the land surface-atmosphere interaction, we hypothesize that vegetation regulates the long-term temperature sensitivity to precipitation change in semi-arid and arid regions. To test this hypothesis, we use a temperature and precipitation dataset complemented with land cover maps and Normalized Difference Vegetation Index (NDVI) dataset in Northwest China mainly to: 1) estimate the sensitivity of near ground air temperature to precipitation change; and 2) investigate the role of land cover in determining the long-term response of near ground air temperature to precipitation change.

2. Materials and method

2.1. Study area and dataset

The study region is located in Northwest China, central Eurasia,

* Corresponding author.
E-mail address: quan.zhang@whu.edu.cn (Q. Zhang).

https://doi.org/10.1016/j.jaridenv.2018.01.015
Received 31 August 2017; Received in revised form 6 January 2018; Accepted 19 January 2018
Available online 01 February 2018
0140-1963/ © 2018 Elsevier Ltd. All rights reserved.

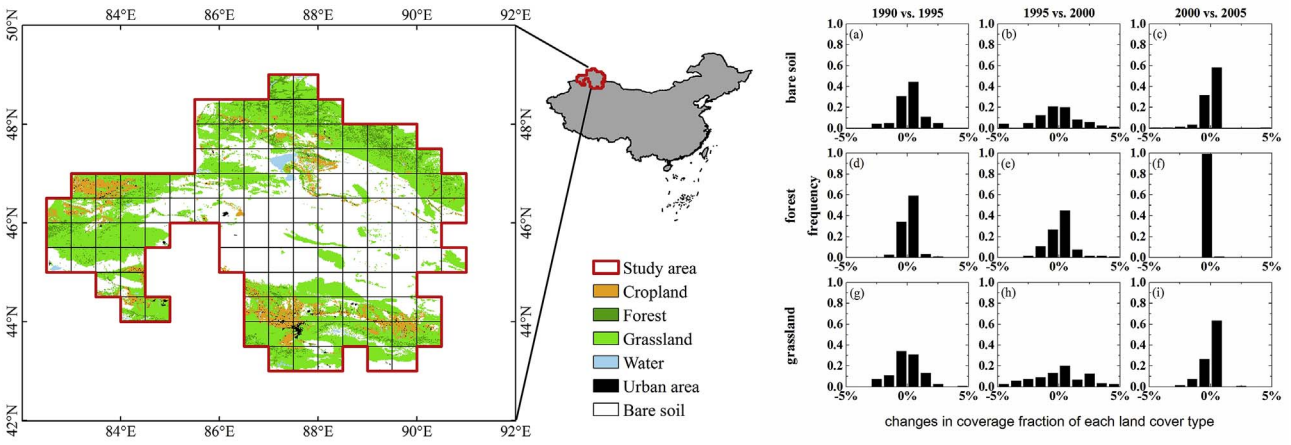

Fig. 1. The study region and the spatial distribution of land cover (left-hand panel); right-hand panel is the frequency distribution of land cover change evaluated by the difference of coverage fraction at pixel level for bare soil (a, b, and c), forest (d, e, and f), and grassland (g, h, and i); the three columns from left to right represent corresponding change of land cover between 1990 and 1995, 1995 and 2000, and 2000 and 2005.

stretching between 43.0–49.0 °N and 82.5–91.0 °E with an area of approximately 3.70×10^5 km^2 (Fig. 1, left-hand panel). The annual precipitation ranges from 110 mm to 550 mm, and the mean annual air temperature ranges from −7 °C to 7 °C. This region is classified as semi-arid with an aridity index below 0.5 according to Global Aridity and PET Database (http://www.cgiar-csi.org/data/global-aridity-and-pet-database). This is an ideal place to explore the temperature and precipitation relationship because it is less affected by the Arctic Oscillation or El Niño–Southern Oscillation (Adler et al., 2008).

To analyze the temperature sensitivity to precipitation, we used monthly mean air temperature observed at 2 m above the ground and monthly total precipitation from the period of 1982–2006 (China Meteorological Data Service Center, http://data.cma.cn/). These two datasets are at a spatial resolution of 0.5° × 0.5° interpolated by thin plate spline (TPS) in ANUSPLIN software based on 2, 472 site measurements and Global 30 Arc-Second Elevation (GTOPO30) data resampling. The assessment reports of precipitation and temperature (NMIC, 2012) showed that the monthly root-mean-square error (RMSE) varies from 0.2 mm to 0.8 mm for precipitation, and the annual RMSE ranges from 0.2 °C to 0.3 °C for temperature. In addition, the datasets have been widely evaluated for reliability and applied in numerous meteorological assessments and environmental impact studies (e.g., Wang et al., 2013; Wu et al., 2017).

Land cover maps of four years (i.e., 1990, 1995, 2000 and 2005) with a spatial resolution of 1 km × 1 km were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The land cover types are classified at two levels, the first level contains 6 broad categories, i.e., cropland, forest, grassland, water body, urban area, and bare soil; the second level details the aforementioned 6 categories into 25 more specific land cover types (see Liu et al., 2003 for details). In the study region, forest, grassland and bare soil account for more than 90% of total area. Hence, in this study we only considered these 3 main land covers on the first level. The coverage fraction of each land cover, defined as the ratio of area between the specified land cover type and the pixel area, was calculated at the pixel level. Evaluations show that land cover did not change much in the past two decades (Fig. 1, right-hand panel). Therefore, we used the mean coverage fraction of the four years to represent the land cover conditions.

To account for the vegetation phenology, we used the continental Global Inventory Modelling and Mapping Studies NDVI dataset (http://glcf.umiacs.umd.edu/data/gimms) with a spatial resolution of 8 km × 8 km and an interval of 15 d (Tucker et al., 2005). We applied the maximum value composite method to generate a monthly NDVI dataset (Holben, 1986) to reduce noise mainly from clouds. The NDVI data were then spatially aggregated to a resolution of 0.5° × 0.5° so that they agreed, geographically, with the temperature and precipitation records.

2.2. Quantifying the temperature sensitivity to precipitation change

The monthly mean temperature and total precipitation were aggregated to the growing season (April through October, typical for Northwest China) at the pixel level (0.5° × 0.5°). We used a linear regression model (Yin et al., 2014) to detect the long-term temperature response to precipitation change,

$$\Delta T = a_0 + a_1 \Delta P \quad (1)$$

where ΔT and ΔP represent the annual mean temperature anomaly (°C) and total precipitation anomaly (mm) in the growing season, respectively; a_0 equals zero because both ΔT and ΔP are anomalies, while the linear regression slope a_1 (°C mm^{-1}) is determined by the least square method. In general, a_1 is negative for semi-arid and arid regions; we defined the sensitivity coefficient β (°C mm^{-1}) as the absolute value of a_1, in order to quantify the temperature sensitivity to precipitation change as,

$$\beta = |a_1| \quad (2)$$

Such correlation analyses were performed at each pixel.

2.3. Investigating the role of vegetation in determining the temperature sensitivity to precipitation change

To investigate how land cover type controls the temperature sensitivity to precipitation change, β was linearly correlated with coverage fraction of forest, grassland, and bare soil, respectively at pixel level,

$$\beta = b_0 + b_1 C_F \quad (3)$$

where b_0 and b_1 are fitting parameters, and C_F is the coverage fraction of the three major land cover types (i.e., forest, grassland and bare soil).

In addition to land cover type, we used NDVI as a surrogate of vegetation dynamics to numerically quantify how vegetation controls the temperature sensitivity to precipitation change; β was then linearly correlated with NDVI as,

$$\beta = c_0 + c_1 \mathrm{NDVI} \quad (4)$$

where c_0 and c_1 are fitting parameters.

The F-test was used throughout this paper to assess the significance of regressions.

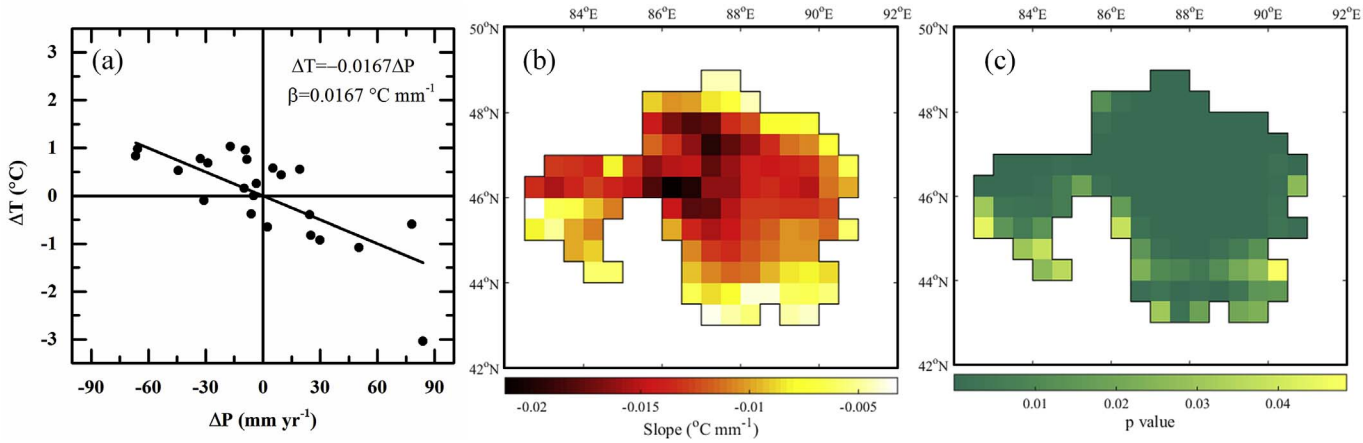

Fig. 2. (a) An example of the relationship between temperature and precipitation from a selected pixel; (b) spatial distribution of the linear regression slope (a_1 in equation (1)) between the temperature (ΔT) and precipitation (ΔP) anomalies in the study area; (c) spatial distribution of the significance level (p-value) of the regression between temperature anomaly (ΔT) and precipitation anomaly (ΔP) in the study area.

3. Results

3.1. Spatial distribution of the temperature sensitivity to precipitation change

The temperature and precipitation anomalies were well correlated (see Fig. 2a, as an example from a selected pixel). Fig. 2b shows the spatial distribution of temperature sensitivity to precipitation change in the study region. In particular, the values of a_1 at these pixels range from -0.021 °C mm^{-1} in the middle of the desert to -0.003 °C mm^{-1} in the surrounding vegetated region. All regressions at these pixels in the study area passed the significance level $p < 0.05$ (Fig. 2c).

3.2. The temperature sensitivity to precipitation change regulated by land cover

The spatial distribution of a_1 (Fig. 2b) agrees well with the distribution of regional land cover types (Fig. 1, left-hand panel), prompting interest in how land cover types control the response of temperature to precipitation change. The results in Fig. 3a show that β correlates linearly with the coverage fraction of each land cover type. The increase in bare soil at the pixel level drives near ground air temperature to become more sensitive to precipitation change; in contrast, a higher coverage fraction of forest and grassland reduces the temperature sensitivity in response to precipitation change. In addition, the slope between β and the coverage fraction of forest is higher than that of grassland, indicating that forest is more efficient in reducing the temperature sensitivity to precipitation change than grassland. However, the correlation for forest is less satisfying as a result of the limited range of the forest coverage fraction.

We also applied NDVI as a surrogate to quantitatively investigate how vegetation phenology controls the temperature sensitivity to precipitation change. Results show that temperature sensitivity to precipitation change correlates negatively with NDVI, indicating that a higher NDVI corresponds to a lower temperature sensitivity to precipitation change (Fig. 3b). These results suggest that vegetation contributes to reducing the temperature sensitivity to precipitation change possibly through land surface feedback mechanisms.

4. Discussion and conclusion

In semi-arid and arid regions where runoff is minimal, precipitation generally dominates vegetation dynamics, which play an important role in the land-atmosphere interaction. The NDVI is commonly used as a metric of vegetation phenology, and previous studies showed that NDVI correlates well with both temperature and precipitation in semi-arid regions (e.g., Weiss et al., 2004). However, such correlations still show contrasting patterns associated with land cover; for example, NDVI and temperature have been found to correlate positively in forest (Bao et al., 2015), but negatively in grassland (Bao et al., 2015; Yuan et al., 2015); while NDVI and precipitation correlate positively in cropland (Camberlin et al., 2007) and grassland (Bao et al., 2015; Yuan et al., 2015), but negatively in forest (Bao et al., 2015). The diverse results among different land covers, on one hand, indicate the complexities of land-vegetation-atmosphere interactions, on the other hand, imply the possible controls of land cover types on temperature and precipitation

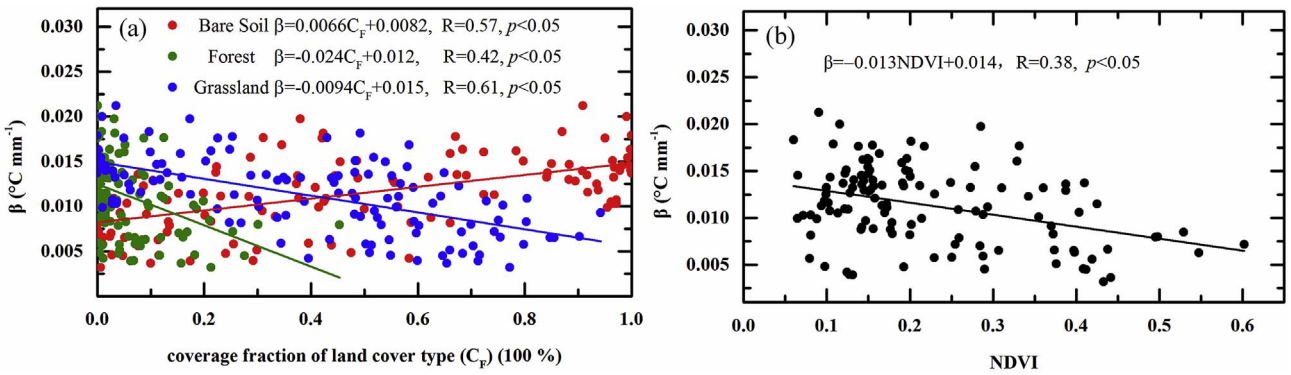

Fig. 3. (a) Correlations of the temperature sensitivity to precipitation change (β) and coverage fraction (C_F) of the three major land cover types - bare soil, forest and grassland; (b) the relationship between β and the long-term averaged NDVI (1982–2006). Note that each sample corresponds to one pixel.

relationship. Given the strong evidence that temperature correlates negatively with precipitation in semi-arid and arid regions regardless of land cover (Yin et al., 2014), these previous efforts to separately correlate NDVI with both precipitation and temperature remain difficult to answer what controls the temperature sensitivity to precipitation change.

By introducing NDVI as a new possible predictor, we showed how temperature sensitivity to precipitation varies with vegetation phenology, and confirmed that temperature of well-vegetated regions is generally less sensitive to precipitation change in semi-arid regions. In particular, one unit increase in NDVI will result in a 0.013 °C mm^{-1} (95% confidence interval is [0.007, 0.018]) decline in the temperature sensitivity to precipitation change. We further found pretty consistent vegetation control on the temperature sensitivity to precipitation when evaluated in different periods (data not shown, but the slopes of β-NDVI relationship were -0.015 and -0.014 °C mm^{-1} in the periods of 1982–1996 and 1992–2006, respectively).

In semi-arid and arid regions, it is well known that temperature generally correlates negatively with precipitation; our results contribute further to show that the temperature sensitivity to precipitation varies with land cover and vegetation phenology. Therefore, the aforementioned evaporative cooling effect associated with the different physical and physiological properties of vegetation (Leuzinger and Körner, 2007) not only impacts the absolute temperature magnitude, but also may mitigate the temperature range by regulating the stomata's opening. These results also highlight the significant role of vegetation in controlling land-atmosphere interaction, and in driving temperature becomes less sensitive to precipitation change in more densely vegetated area.

These results have broad implications in ecological management and in land surface model evaluations by diagnosing the role of vegetation in controlling land-atmosphere interaction. In addition to the direct effects of vegetation as shown in this study, other factors may have indirect effects on the temperature sensitivity to precipitation change. For example, topography controls vegetation distribution, therefore, may indirectly impacts the temperature sensitivity to precipitation change. A major limitation of this analysis is the difficulty to address direct effects of the land-atmosphere interaction, which may be further explored using physically-based models in future studies.

Acknowledgement

We appreciate the constructive comments from two anonymous reviewers. This research was supported by the National Natural Science Foundation of China (Project NOs. 51509187, 51525902 and 91547205) and National Key R&D Program of China (Grant NO. 2016YFC0402708). The temperature and precipitation data can be found at http://cdc.nmic.cn/home.do, the land cover map can be found at http://www.resdc.cn.

References

Adler, R.F., Gu, G., Wang, J.J., Huffman, G.J., Curtis, S., Bolvin, D.T., 2008. Relationships between global precipitation and surface temperature on inter-annual and longer time scales (1979-2006). J. Geophys. Res. 113, D22104. http://dx.doi.org/10.1029/2008JD010536.

Bao, G., Bao, Y.H., Sanjjava, A., Qin, Z.H., Zhou, Y., Xu, G., 2015. NDVI-indicated long-term vegetation dynamics in Mongolia and their response to climate change at biome scale. Int. J. Climatol. 35, 4293–4306. http://dx.doi.org/10.1002/joc.4286.

Bonan, G.B., 1997. Effects of land use on the climate of the United States. Clim. Change 37, 449–486. http://dx.doi.org/10.1023/A:1005305708775.

Camberlin, P., Martiny, N., Philippon, N., Richard, Y., 2007. Determinants of the inter-annual relationships between remote sensed photosynthetic activity and rainfall in tropical Africa. Remote Sens. Environ. 106, 199–216. http://dx.doi.org/10.1016/j.rse.2006.08.009.

Findell, K.L., Pitman, A.J., England, M.H., Pegion, P., 2009. Regional and global impacts of land cover change and sea surface temperature anomalies. J. Clim. 22, 3248–3269. http://dx.doi.org/10.1175/2008JCLI2580.1.

Holben, B.N., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Rem. Sens. 7, 1417–1434. http://dx.doi.org/10.1080/01431168608948945.

Leuzinger, S., Körner, C., 2007. Tree species diversity affects canopy leaf temperatures in a mature temperate forest. Agric. For. Meteorol. 146, 29–37. http://dx.doi.org/10.1016/j.agrformet.2007.05.007.

Liu, J., Liu, M., Zhuang, D., Zhang, Z., Deng, X., 2003. Study on spatial pattern of land-use change in China during 1995–2000. Sci. China Earth Sci. 46 (4), 373–384.

NMIC (National Meteorological Information Center), 2012. Assessment Report of China's Ground Precipitation and Temperature 0.5°×0.5° Gridded Dataset (V2.0). National Meteorological Information Center, Beijing (in Chinese).

Peng, S., Piao, S., Zeng, Z., Ciais, P., Zhou, L., Li, L.Z.X., Myneni, R.B., Yin, Y., Zeng, H., 2014. Afforestation in China cools local land surface temperature. Proc. Natl. Acad. Sci. U.S.A. 111, 2915–2919. http://dx.doi.org/10.1073/pnas.1315126111.

Pielke, R.A., Avissar, R., Raupach, M.R., Dolman, A.J., Zeng, X., Denning, A.S., 1998. Interactions between the atmosphere and terrestrial ecosystems: influence on weather and climate. Global Change Biol. 4, 461–475. http://dx.doi.org/10.1046/j.1365-2486.1998.t01-1-00176.x.

Shen, M., Piao, S., Jeong, S.J., Zhou, L., Zeng, Z., Ciais, P., Chen, D., Huang, M., Jin, C.S., Li, L.Z., 2015. Evaporative cooling over the Tibetan Plateau induced by vegetation growth. Proc. Natl. Acad. Sci. U.S.A. 112, 9299–9304. http://dx.doi.org/10.1073/pnas.1504418112.

Stott, P., 2016. How climate change affects extreme weather events. Science 352, 1517–1518.

Tucker, C.J., Pinzon, J.E., Brown, M.E., Slayback, D., Pak, E.W., Mahoney, R., Vermote, E., El Saleous, N., 2005. An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. Int. J. Rem. Sens. 26, 4485–4498. http://dx.doi.org/10.1080/01431160500168686.

Wang, K.C., Dickinson, R.E., 2012. A review of global terrestrial evapotranspiration: observation, modeling, climatology, and climatic variability. Rev. Geophys. 50http://dx.doi.org/10.1029/2011RG000373. RG2005.

Wang, S., Zhang, M., Sun, M., Wang, B., Li, X., 2013. Changes in precipitation extremes in alpine areas of the Chinese Tianshan Mountains, central Asia, 1961–2011. Quat. Int. 311, 97–107. http://dx.doi.org/10.1016/j.quaint.2013.07.008.

Weiss, J.L., Coonrod, J.E.A., Dahm, C.N., Gutzler, D.S., 2004. Seasonal and inter-annual relationships between vegetation and climate in central New Mexico, USA. J. Arid Environ. 57, 507–534. http://dx.doi.org/10.1016/S0140-1963(03)00113-7.

Wu, X., Wang, Z., Zhou, X., Lai, C., Chen, X., 2017. Trends in temperature extremes over nine integrated agricultural regions in China, 1961–2011. Theor. Appl. Climatol. 129, 1279–1294. http://dx.doi.org/10.1007/s00704-016-1848-0.

Yin, D.Q., Roderick, M.L., Leech, G., Sun, F.B., Huang, Y.F., 2014. The contribution of reduction in evaporative cooling to higher surface air temperatures during drought. Geophys. Res. Lett. 41, 7891–7897. http://dx.doi.org/10.1002/2014GL062039.

Yuan, X.L., Li, L.H., Chen, X., Shi, H., 2015. Effects of precipitation intensity and temperature on NDVI-based grass change over Northern China during the period from 1982 to 2011. Rem. Sens. 7, 10164–10183. http://dx.doi.org/10.3390/rs70810164.